An Efficient Fruit Identification and Ripening Detection Using CNN Algorithm

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ABSTRACT

Effective and efficient fruit detection is considered crucial for designing automated robot (AuRo) for yield estimation, disease control, harvesting, sorting, and grading. Several fruit detection schemes for designing AuRo have been developed during the last decades. However, conventional fruit detection methods are deficient in the real-time response, accuracy, and extensibility. This paper proposes an improved multi-task cascaded convolutional network-based intelligent fruit detection method. This method has the capability to make the AuRo work in real time with high accuracy. Moreover, based on the relationship between the diversity samples of the dataset and the parameters of neural networks' evolution, this paper presents an improved augmented method, a procedure that is based on image fusion to improve the detector performance. The experiment results demonstrated that the proposed detector performed immaculately both in terms of accuracy and time–cost. Furthermore, the extensive experiment also demonstrated that the proposed technique has the capacity and good portability to work with other akin objects conveniently. the chloroplast is responsible for providing the green colour in the plant. Where is the chromoplast its various types of colours in the plant.there is a change from Green to yellow colour in most of the fruit. This is due to the overgrowth of the chromoplast by replacement of the chloroplast hence there is feeding of the green colour and prominence of the yellow colour. The change of colour of unripe green fruit from green to red is because of the transformation of chloroplast to chromoplast because in immature stage chloroplast is green in colour while on maturation the chloroplast disappears and chromoplast containing carotenoids which impart red colour.

Index Terms: Fruit detection, automated robots, real-time processing, multi-task cascaded convolutional network, image fusion, chloroplast, chromoplast, color transition, carotenoids.

1. INTRODUCTION

Fruit detection for yield estimation, grade sorting, disease control and other applications in agricultural field have achieve intensive popularity over the past few decades [1]–[5]. Several systems have been deployed for automated harvesting robots, which have led to considerable improvement in the industry

[6], [7]. Particularly, recognizing and classifying fruits according to their quality has been one of the most popular research fields attracting most of the farm enterprises. Fruit detection is undoubtedly the first and foremost parameter to be considered in order carry out more in-depth studies on the subject. Therefore, many researchers have made efforts for years to develop robust algorithm for fruit detection [8]–[10]. Although, the performance of fruit detection systems has been improved remarkably, they are still far from practical application. The basic difficulties in developing such fruit detection system are the uncertain and unrestrained environments of orchards. These include numerous challenging tasks, such as insufficient or over illumination, indistinguishable backgrounds, heavy occlusion by neighborhood fruits or foliage, low-resolutions, variation of pose and so on.

Fruit detection can be considered a special type of object detection that has many similarities with face detection task [11]–[13]. Due to the advantage of high precision, cascaded convolutional networks (CCN) based face detection has acquired a remarkable breakthrough [14], [15]. Among these state-of-the-art methods, multi-task cascaded convolutional network (MTCNN) [16] is the most popular one due to its outstanding performance in accuracy and time consumption. Although MTCNN has achieved great progress in face detection task, deploying this method directly for fruit detection task is not suitable. It is due to the design of MTCNN, that its architecture includes many specificity functions for face detection, which are not suitable for the task of fruit detection. Thus, there is a need to improve this MTCNN framework by removing customized functionality.

The absence of a unified benchmark is another great challenge for fruit detection. A sufficient amount of sample images plays an important role in deep learning based model training. In this research, we collected images from apple orchard by digital camera. Then we selected the suitable ones and labeled them to create a dataset. Creating a dataset manually is a tedious and time-consuming task. So we devised a new augmented method based on fusion algorithm. The motivation for this fusion method came from the principle that the generated new samples should be close to authentic images. Supplementary samples were created for diversity by adding fusion images that would help improve the final result of this detector. In order to evaluate the structure whether it could be applied to other kinds of objects conveniently, we trained the detector on two other fruits species (strawberry and orange) as well

To summarize, our contributions are as follows:

1. We proposed a new architecture for fruit detection called Fruit-MTCNN (F-MTCNN) by improving the baseline model of MTCNN. And this detector has the attributes of high accuracy and less time-consumption.

2. We proposed a novel augmented method called fusion augmentation (FA). We generate artificial images samples by adding negative patches from samples of dataset by random cropping that supplement the samples diversity.

3. The proposed approach can be deployed to other kinds of objects conveniently with a

small amount of training samples.

Automated harvesting robot is a potential solution for many challenges in agriculture such as the explosively increasing global old-age population, labor cost increase, increasing demand for of produce and so on. Identify and obtaining precise positions of fruits are the most important parts of the visual system for a harvesting robot. Due to this reason, fruits identification and detection has been extensively studied for years. Generally, these methods can be divided into three types by the technologies they employ.

2. IMAGE PROCESSING

Several image processing techologies are in use for fruit detection task [17]–[20]. For example, Aggelopoulou et al. [21] proposed an algorthim based on binary image technology for flower images of apple tree, and analyzed the correlation between yield and flower density. To segment branches from images, Ji et al. [22] converted RGB color space to I1I2I3 and XYZ space by a transformation formula. Several classification techniques such as decision trees, K-nearest neighbor, and discriminant analysis image processing algorithms are used to choose appropriate wavelengths to classify images of codling moth infestation in apples [23]. To improve fruit detection, Bulanon et al. [24] proposed an image fusion method by obtaining thermal and visible images simultaneously. Moreover, the experiments on an orange canopy scene of orchard showed that this approach improved fruit detection compared to the one that only used thermal images. In general, these methods need to design a special algorithm for a specific task, and they are highly dependent upon the characteristics of the subject, which needs to be redesigned if there is a slight change in its condition. Therefore, the weaknesses in these methods hardly satisfy requirements of a farm manager.

3.MACHINE LEARNING

There are some machine learning based techologies for detection tasks, such as those reported in [25]–[30]. To detect and count immature citrus fruits, Lu et al. [9] extracted features of local binary pattern (LBP) and detected local intensity maxima around the immature fruits. Benalia et al. [31] developed a system to improve the quality control and sorting of dried fruits of fig (Ficus carica). These approaches employ computer vision techniques such as PLS-DA and PCA to analyze images and get better result ultimately. Borges et al. [32] also presented a classification system based on clustering. This technique was applied to classify the severity of bacterial spot in tomato filed. All these machine based learning methods greatly improved the detection performance. However, the shortcomings were that the features they used were extracted through experienced worker. In addition, the high performance achieves by these machine learning based methods was at the cost of high computational complexity. Therefore, there was a need to search for and find out some new procedures that would extract features automatically.

4.DEEP LEARNING

Over the past few years, deep neural networks procedures have made a considerable progress in many fields [33]. Wireless communication [34], [35], signal processing [36]–[38], image classification [39], saliency detection [40]–[44]. Many approaches have been developed in the field of agriculture as well [45]–[48]. Bargoti and Underwood [49] presented an approach for fruit detection and counting using images taken in orchard. They used two feature learning algorithms i.e. multi-scale Multi-Layered Perceptrons and Convolutional Neural Networks (CNN), to segment the fruit from its background. Their final results showed the performance closer to the state-of-the-art perfection. Faster-RCNN is one of the most advanced object detection methods, has provided good results in many detection tasks [50]. Recently, a FasterRCNN framework approach was adopted for fruit detection for mango, almond and apple in orchards [51]. This method also showed that data augmentation can signify performance and reduce training images by more than two-folds. The final result presented that this approach accomplished a remarkable detection performance for apples and mangoes. Similarly, Sa et al. [52] also used Faster-RCNN as a baseline fruit detector. The difference is they used imagery obtained from these two modalities i.e. Color and Near-Infrared. Thus they proposed a new approach by combining these two kinds of information earlier or later. This proposed multi-modal approach provides better performance compare to prior work. However, using Faster-RCNN architecture for fruit detection directly is inadequate. This is because the Faster-RCNN designed detection task for many categories of objects with large scale change. Whereas, the visual system in agriculture needs to detect one or only a few kinds of fruit in general, and usually the fruit size does not change significantly. Thus, the application of Faster-RCNN model for fruit detection task is complicated and time-consuming. Furthermore, providing a large amount of data is necessary to prevent overfitting problems, because the structure of Faster-RCNN is of a deeper architecture that contains thirteen convolution layers. During the recent years, due to the rapid development of security, intelligent equipment and other applications, the detection accuracy has been highly improved.

MOTIVATION

There are many similarities between face detection and fruit detection, such as various poses, illuminations and occlusions. Nevertheless, there are some differences as well between both of them. Firstly, compared with facial features (eyes, nose, mouth), the information contained in fruit is usually relatively simple. In general, the fruit feature only includes the overall information (shape, color). Secondly, it is more likely to be confronted with heavy occlusion in the tasks of fruit detection. Thirdly, there is no uniform benchmark for fruit detection, and sufficient images acquisition and annotation are time-consuming tasks. Finally, real-time is one of the most important indices for fruit detection. This is because fruit detection model is generally applied to automatic equipment, such as picking robot, sorting robot, yield estimation robot and so on. So, for the design of fruit detection model, the above mentioned motives should be taken into consideration.

Based on all that, we designed a fruit detector that can detect fruits with different pose, low resolution and occlusion

5.SYSTEM ARCHITECTURE

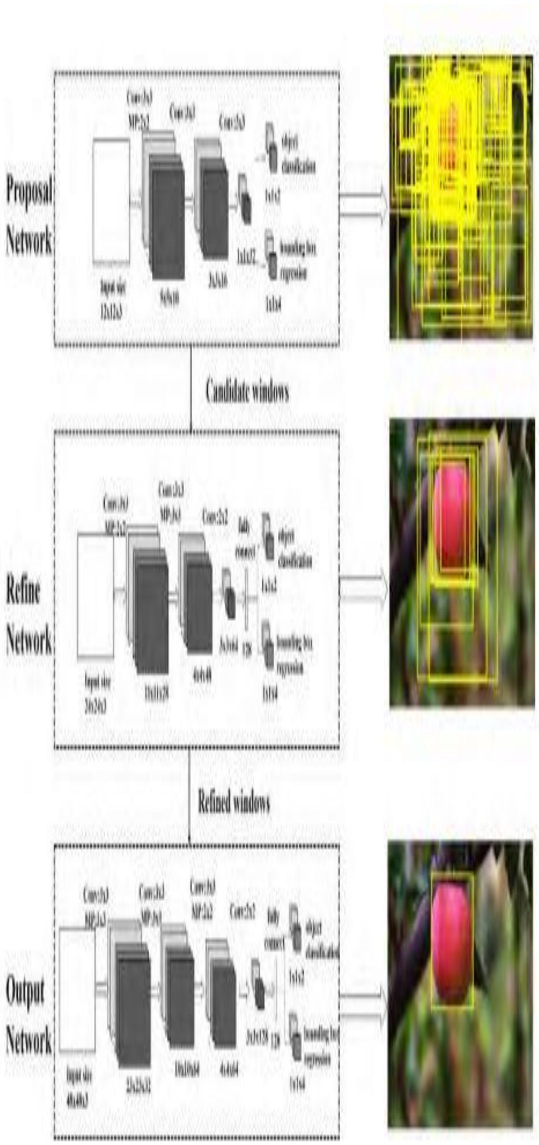

Figure.1. **System Architecture**

5.1 EXISTING SYSTEM

In this paper author is designing Multi-Task Cascaded Convolution Neural Network to build fruit detection model as this network is good at face detection so author applying same MTCNN model to build fruit detection model. This model will accept tree images as input and then detect 3 different types of fruit such as Apple, Strawberry and Oranges. The author has used own fruit dataset which he has capture with his digital camera and he has not publish this dataset on internet so to build MTCNN model we have 360 degree fruit dataset from KAGGLE

5.2 PROPOSED SYSTEM

We presents an improved augmented method, a procedure that is based on image fusion to improve the detector performance. The experiment results demonstrated that the proposed detector performed immaculately both in terms of accuracy and time–cost. Furthermore, the extensive experiment also demonstrated that the proposed technique has the capacity and good portability to work with other akin objects conveniently. the chloroplast is responsible for providing the green colour in the plant. Where is the chromoplast its various types of colours in the plant. there is a change from Green to yellow colour in most of the fruit. This is due to the overgrowth of the chromoplast by replacement of the chloroplast hence there is feeding of the green colour and prominence of the yellow colour. The change of colour of unripe green fruit from green to red is because of the transformation of chloroplast to chromoplast because in immature stage chloroplast is green in colour while on maturation the chloroplast disappears and chromoplast containing carotenoids which impart red colour.

5.3 IMPLEMENTATION: MODULES:

5.3.1. Upload Fruit Train Images Dataset

'dataset' folder and then click on 'Select

Folder' to upload dataset images check image process successfully I am displaying one sample processed image from dataset.

5.3.2. Generate & Load MTCNN Model

In this Module screen MTCNN model generated and we got TPR and TNR which means MTCNN prediction on test data is 100% and false prediction rate is 0% and in below graph we can see MTCNN accuracy and loss.

5.3.3. Upload Test Image & Fruit Detection

uploading '1.jpg' image and then click on 'Open' button MTCNN detected fruit and surround them with bounding boxes.

6.MODULES USED IN PROJECT

6.1 TENSOR FLOW

Tensor Flow is a free and open-source software library for dataflow and differentiable programming across a range of tasks. It is a symbolic math library, and is also used for machine learning applications such as neural networks. It is used for both research and production at Google.

TensorFlow was developed by the Google Brain team for internal Google use. It was released under the Apache 2.0 open-source license on November 9, 2015.

6.2 NUMPY

Numpy is a general-purpose array-processing package. It provides a high-performance multidimensional array object, and tools for working with these arrays.

It is the fundamental package for scientific computing with Python. It contains various features including these important ones:

- A powerful N-dimensional array object
- Sophisticated (broadcasting) functions
- Tools for integrating C/C++ and Fortran code
- Useful linear algebra, Fourier transform, and random number capabilities

- Besides its obvious scientific uses, Numpy can also be used as an efficient multi-dimensional container of generic data. Arbitrary data-types can be defined using Numpy which allows Numpy to seamlessly and speedily integrate with a wide variety of databases.

6.3 PANDAS

Pandas is an open-source Python Library providing high-performance data manipulation and analysis tool using its powerful data structures. Python was majorly used for data munging and preparation. It had very little contribution towards data analysis. Pandas solved this problem. Using Pandas, we can accomplish five typical steps in the processing and analysis of data, regardless of the origin of data load, prepare, manipulate, model, and analyze. Python with Pandas is used in a wide range of fields including academic and commercial domains including finance, economics, Statistics, analytics, etc.

6.4 MATPLOTLIB

Matplotlib is a Python 2D plotting library which produces publication quality figures in a variety of hardcopy formats and interactive environments across platforms. Matplotlib can be used in Python scripts, the Python and IPython shells,the Jupyter Notebook , web application servers, and four graphical user interface toolkits. Matplotlib tries to make easy things easy and hard things possible. You can generate plots, histograms, power spectra, bar charts, error charts, scatter plots, etc., with just a few lines of code. For examples, see the sample plots and thumbnail gallery.

For simple plotting the pyplot module provides a MATLAB-like interface, particularly when combined with IPython. For the power user, you have full control of line styles, font properties, axes properties, etc, via an object oriented interface or via a set of functions familiar to MATLAB users

6.5 SCIKIT – LEARN

Scikit-learn provides a range of supervised and unsupervised learning algorithms via a consistent interface in Python. It is licensed under a permissive simplified BSD license and is distributed under many Linux distributions, encouraging academic and commercial use.

7.RESULTS

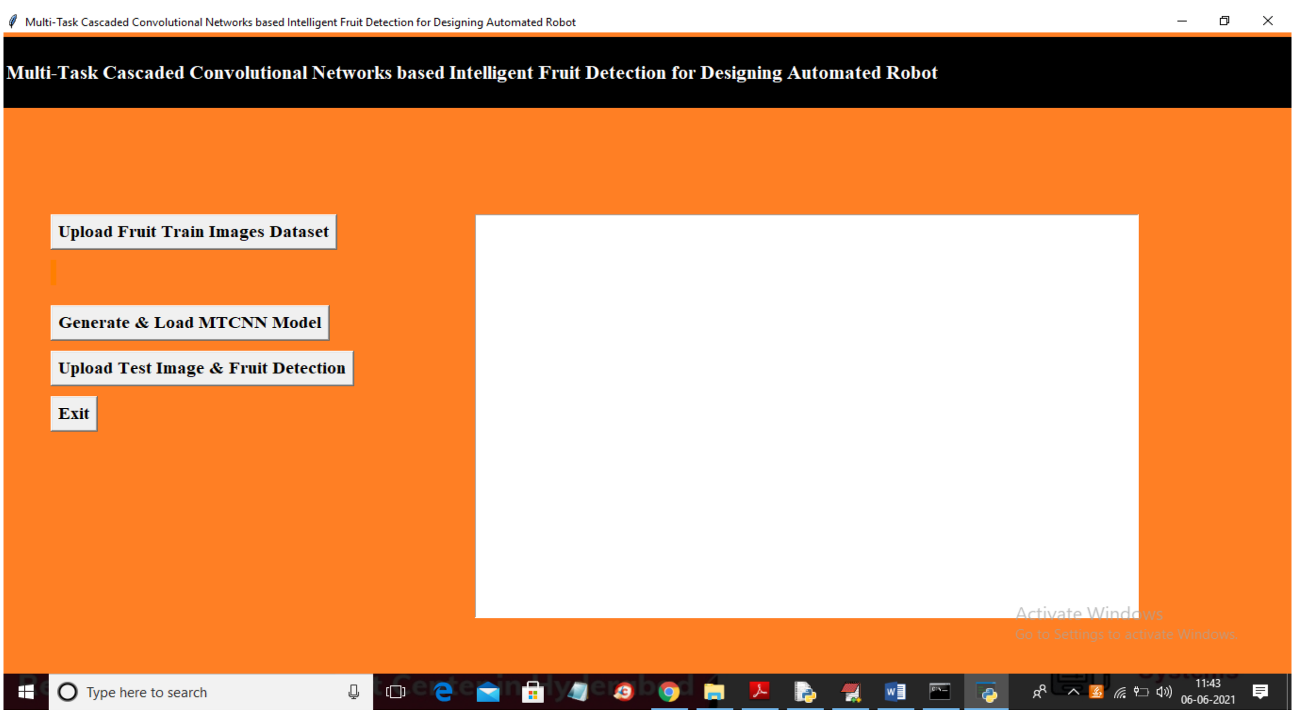

Figure.2. Upload Fruit image screen

In above screen click on 'Upload Fruit Train Images Dataset' button to load dataset

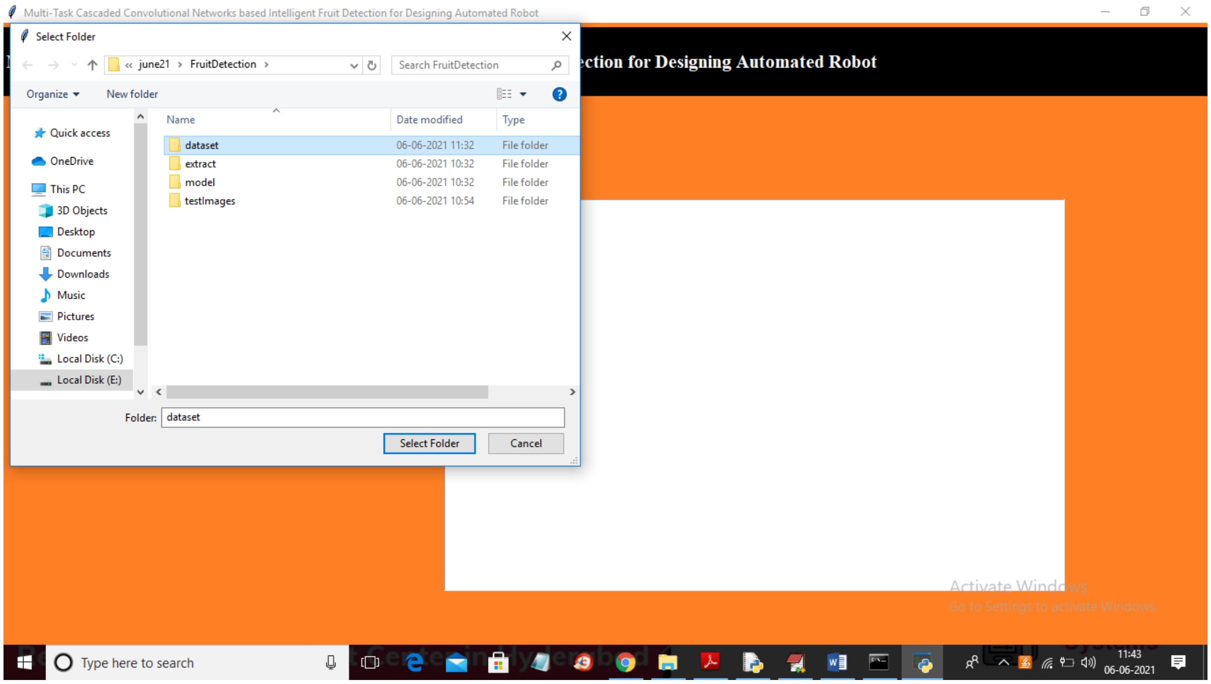

Figure.3. Upload Dataset folder screen

In above screen selecting and uploading 'dataset' folder and then click on 'Select Folder' to upload dataset images and to get below screen

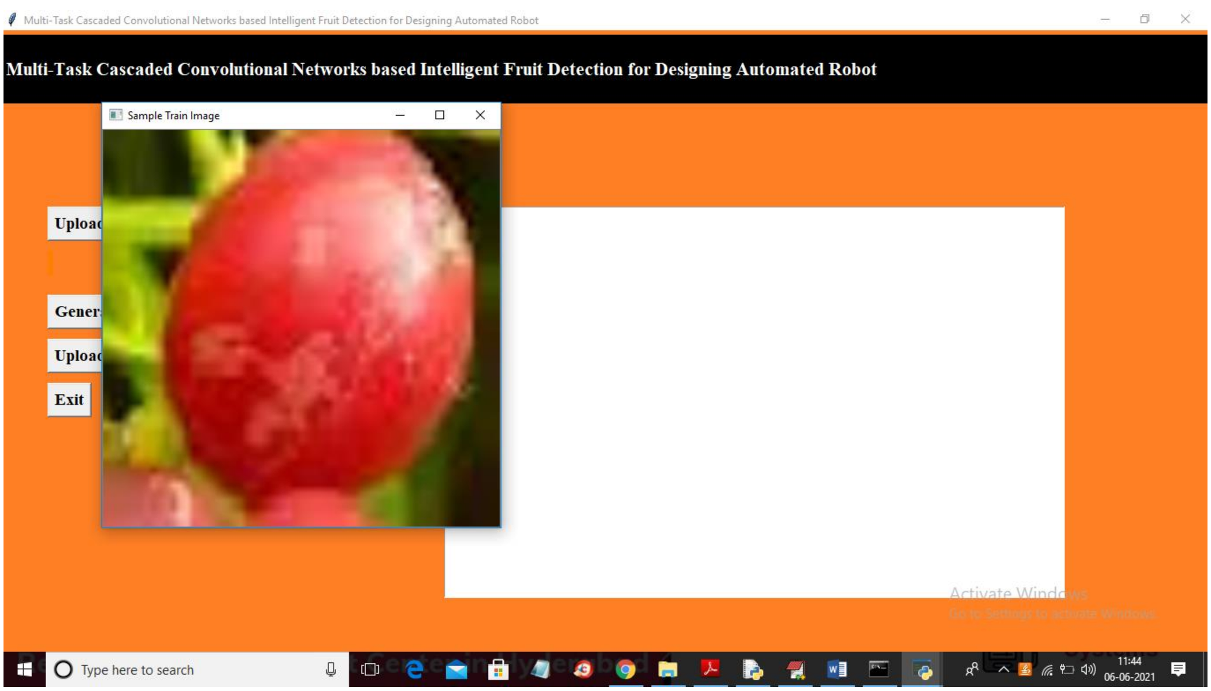

Figure.4 image processed screen

In above screen dataset images loaded and to check image process successfully I am displaying one sample processed image from dataset and now close above image to get below screen

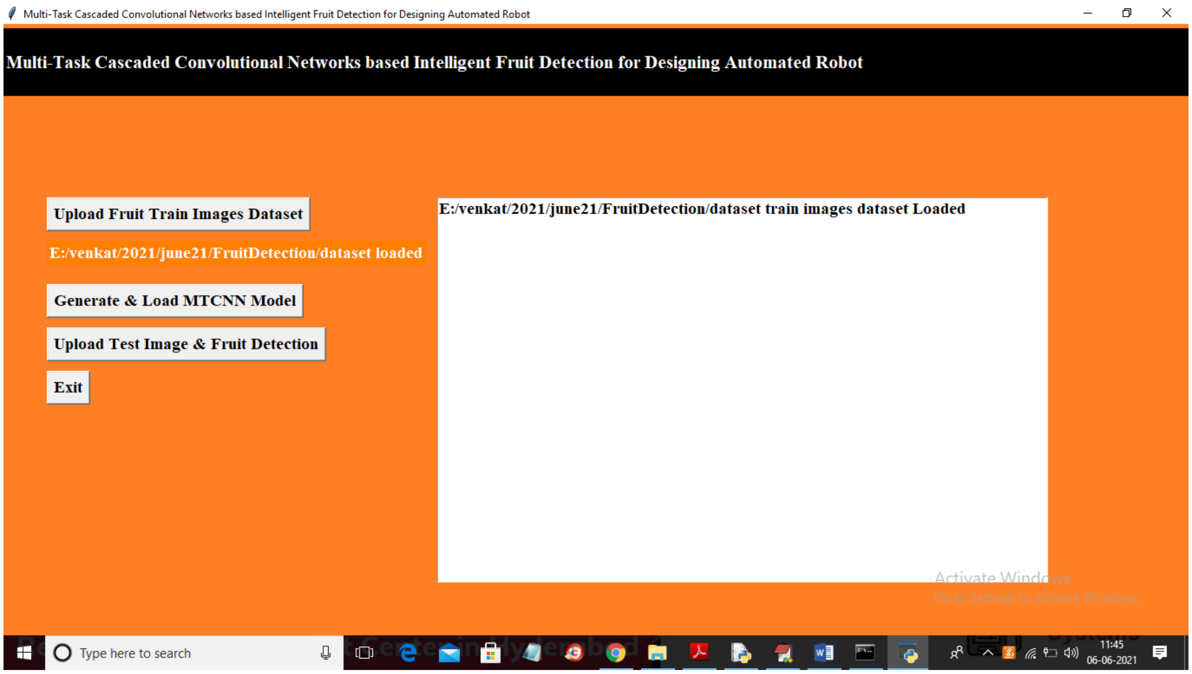

Figure.5.Generate & Load MTCNN Model screen

In above screen dataset loaded and now click on 'Generate & Load MTCNN Model' button to generate and load model

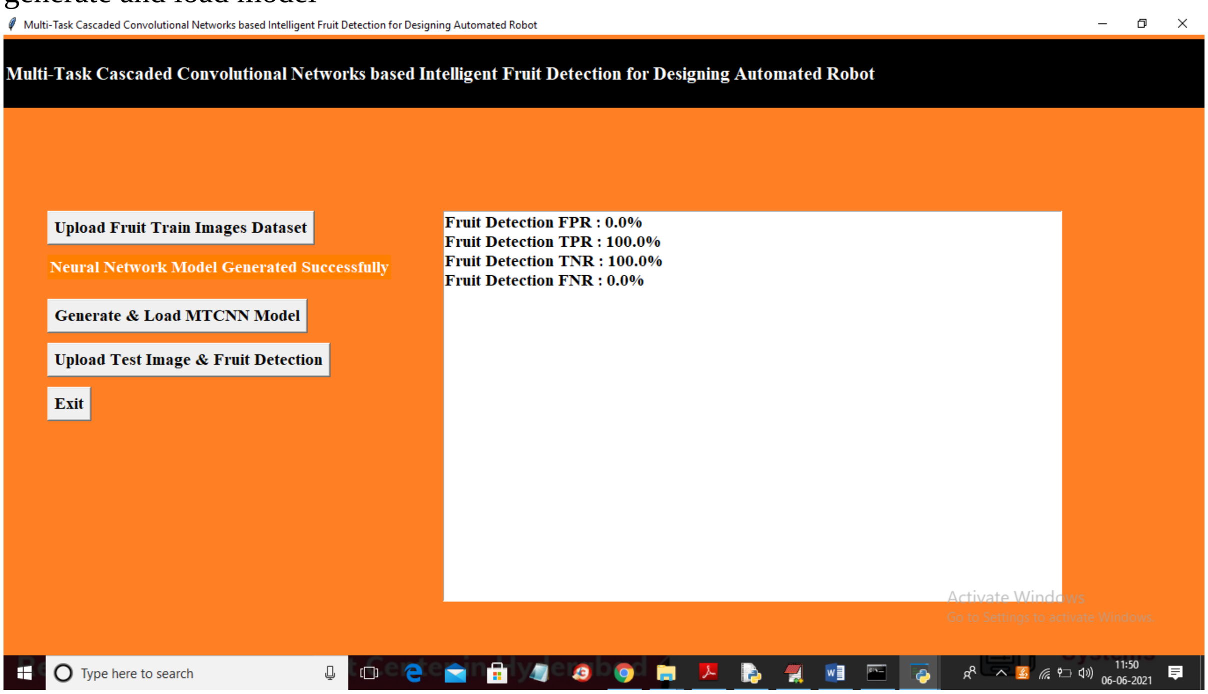

Figure.6.MTCNN mode screen

In above screen MTCNN model generated and we got TPR and TNR which means MTCNN prediction on test data is 100% and false prediction rate is 0% and in below graph we can see MTCNN accuracy and loss

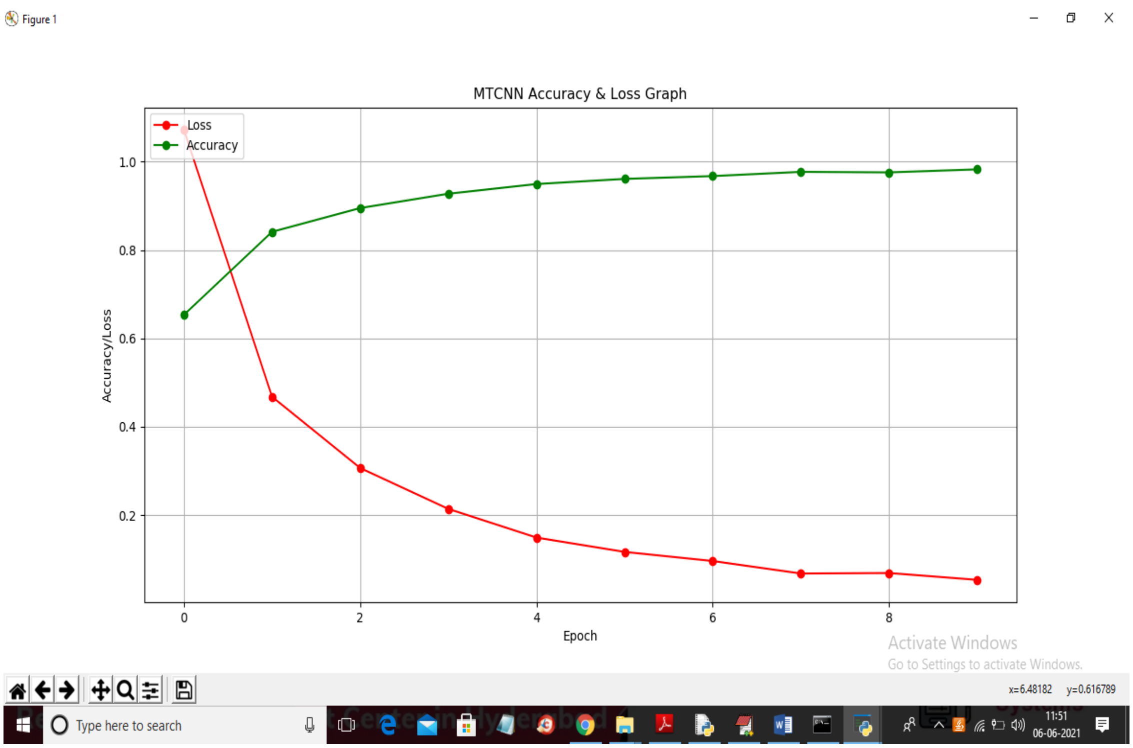

Figure.7.MTCNN Accuracy & Loss Graph

In above graph x-axis represents MTCNN epoch and y-axis represents accuracy and loss value and in above graph red line represents loss and green line represents accuracy and with each increasing epoch we can see loss value decrease and accuracy get increase closer to 100%. Now close above graph and then click on 'Upload Test Image & Fruit Detection' button to upload test image and then get fruit detection output

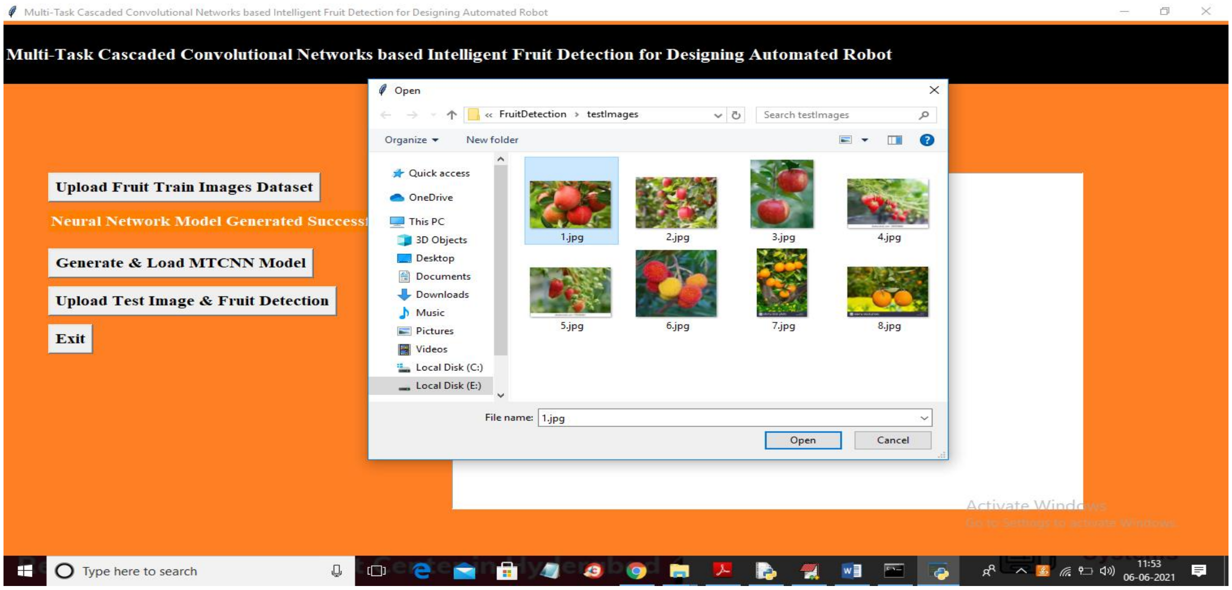

Figure.8.selecting and uploading image

In above screen selecting and uploading '1.jpg' image and then click on 'Open' button to get below result

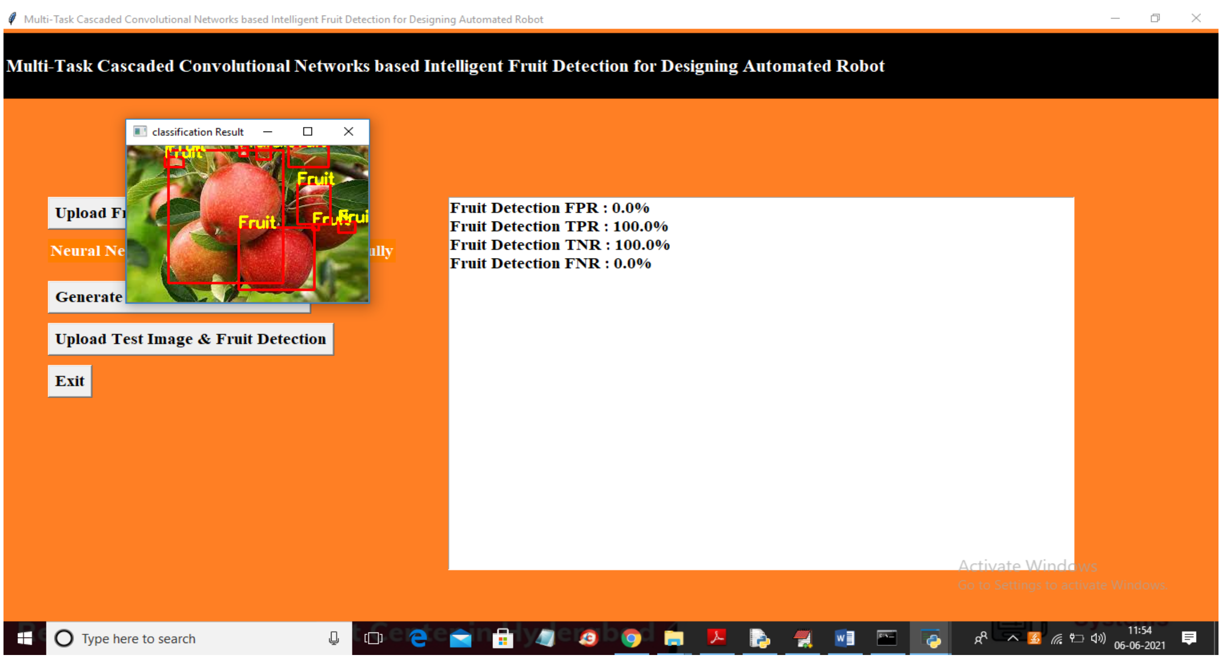

Figure.9. MTCNN detected fruit

In above screen we can see MTCNN detected fruit and surround them with bounding boxes. Test other image

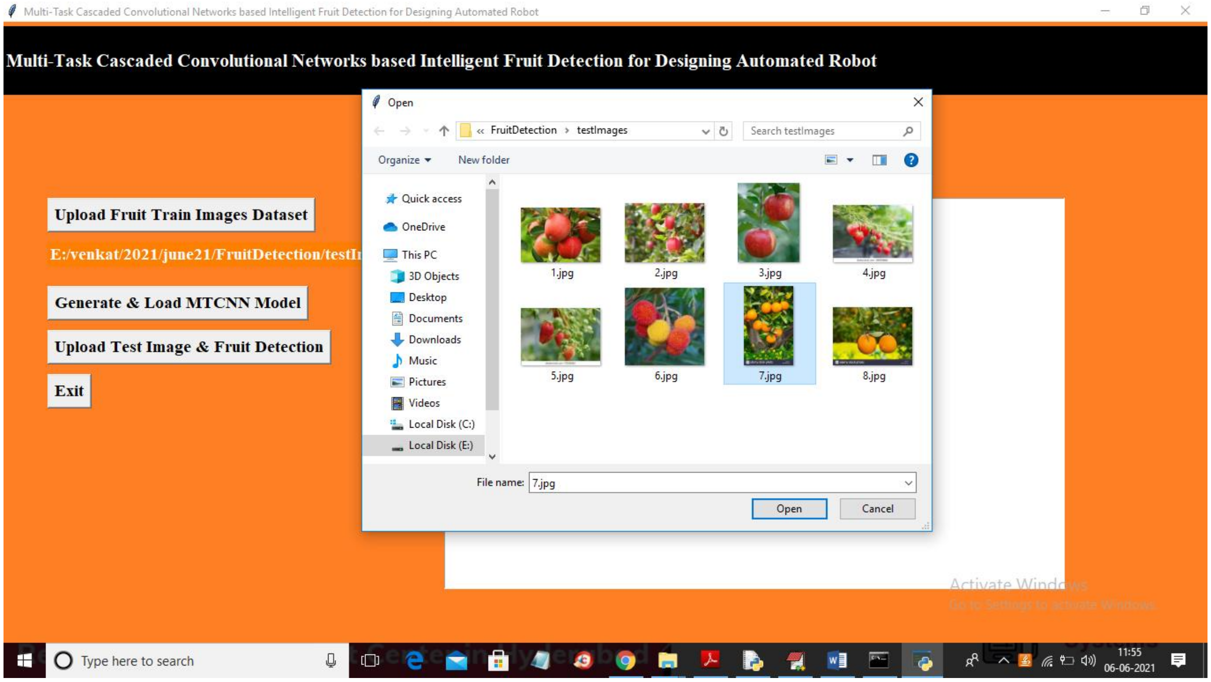

Figure.9. uploading 7.jpg

In above screen uploading '7.jpg' below is the result

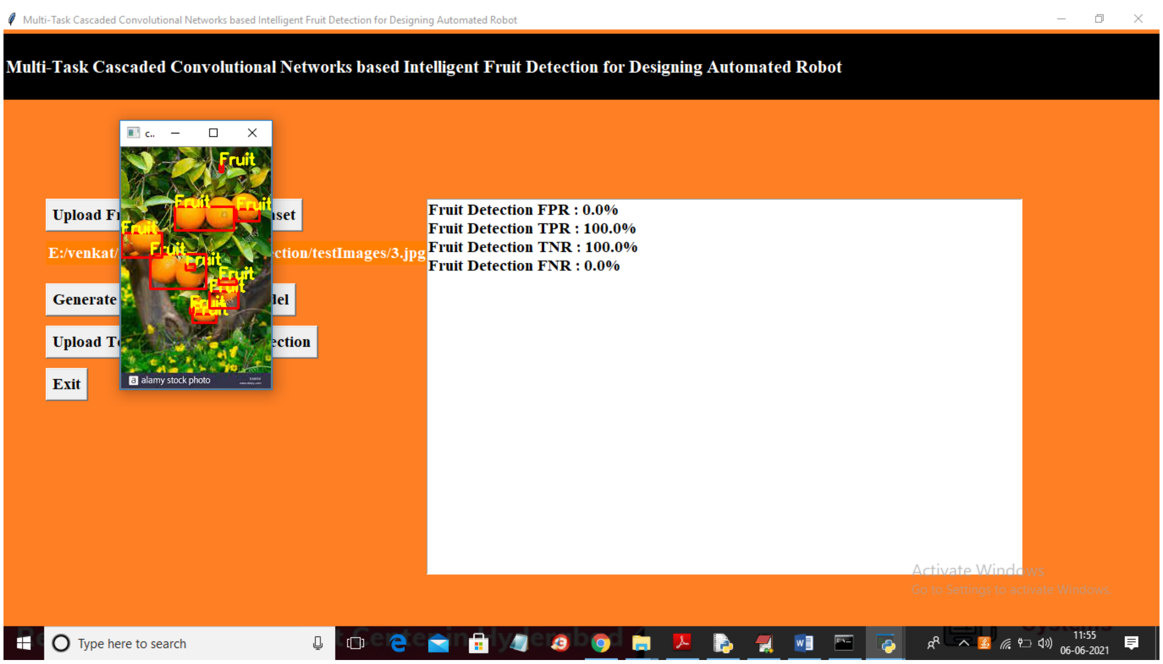

Figure.9. results

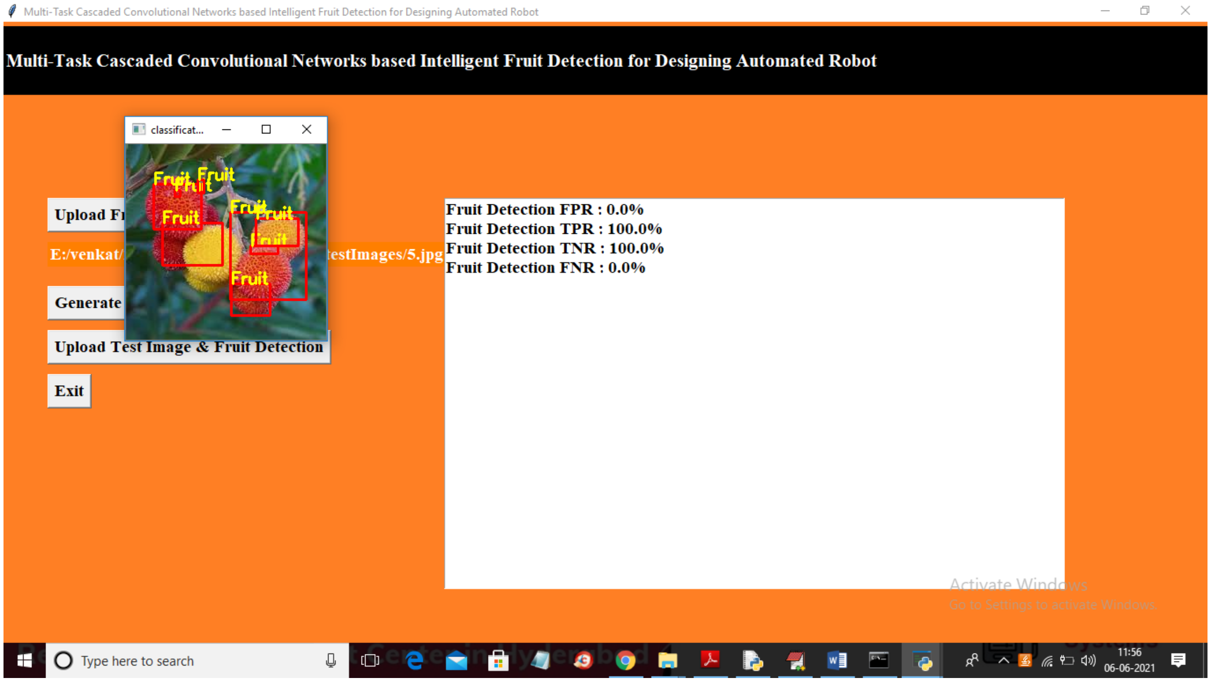

Figure.10. results

Similarly you can test with other images also

8.CONCLUSION

In this study, we exploited a multi-task cascaded convolutional networks based detector for fruit detection. We chose apple for our study and collected more than one thousands of images from apple orchards and labeled them. Alongside this, we also added an appropriate amount of supplementary images from internet and ImageNet dataset to create a dataset. Furthermore, we proposed a novel augmented method called fusion augmentation. The comparative experiment results demonstrated that this augmented method can improve the final result. To verify whether the detector could be applied to other kinds of fruits as well, we selected strawberry and orange as two other test fruits. The dataset for training was obtained from ImageNet dataset, which contains hundreds of images. Our results showed that the detector can conveniently adapt to other kinds of fruit as well. Finally, we tested the detector on twelve groups of images with different resolutions. Each group had one hundred images. The average time cost of the detector was less than 80 seconds per one hundred images, which is very close to real-time response.

9.FUTURE WORK

We find proposed multi-task cascaded convolutional networks based fruit detector have good performance of timeliness and accuracy to meet the requirements for the visual system of harvesting robot from the experimental results. However, there is still a long distance for practical application and promotion of the harvesting robot. One of the most important task is to determine the order for all detected fruits. In other words, is to decide which object should be first considered for picking. Compared with picking manually, by human visual attention can solve this kind of problem effectively. On the basis of this study, we will focus on the study and mimic the human visual attention when viewing the scene by relevant studies such as visual saliency detection and semantic segmentation.

In future, we will also study the characteristics of fruit deeply and design a more reasonable and effective network model for fruit recognition tasks. Besides this, improving and optimizing the accuracy of the detector is also an important task for the future.

10.REFERENCES

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